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Wavelets for QRS Detection.

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Abstract-- This paper examines the use of wavelets for the detection of QRS complex in ECG. Wavelets provide temporal and spectral information simultaneously and offer flexibility with a choice of wavelet functions with different properties. This research has examined wavelet functions with different properties to determine the effects of wavelet properties such as linearity and time/ frequency localization on the accuracy of QRS detection. The sum of false negatives and false positives (total error in detection) is the criterion for determining the efficacy of the wavelet function. The paper reports a significant reduction in error in detection of QRS complexes with mean error reduced to 0.75%. This is achieved with the use of Cubic Spline wavelet- a biorthogonal third order wavelet. This paper reports that the use of wavelets reduces the error in detection of QRS complexes and that wavelet functions that support symmetry and compactness provide better results.

Index Terms–: ***ECG, QRS detection, Wavelet***

I. INTRODUCTION

Accurate detection of QRS is of vital importance in number of clinical instruments. But even though the QRS complex is the dominant feature of the ECG signal and detection of this can be done rather easily by the trained eye of a Cardiologist, the problem of automation of this process is not simple and is complicated due to the fact that morphologies of many normal as well as abnormal QRS complexes differ widely. The presence of noise from many sources make this problem more complex. Further, other sections of ECG (P and T waves) can hinder the detection of QRS complexes and often result in error in classification. Research has determined a number of techniques to detect the QRS complex [3,4,5] and these techniques are used in commercially available equipment.

In general, the commercially used equipment that detect QRS complex require bandpass filtering and temporal filtering (time windowing) of the signal. But the selection of the bandwidth of the filter and the duration (width) of the sliding window is not a simple decision [2,7], the choice of bandwidth is a tradeoff between noise and high frequency details while duration of the sliding window is a tradeoff between false and missed detections. Further, the bandwidth of the signal and duration of the QRS complex are dynamic varying and fixed values of either are not suitable for QRS complex detection.

Researchers have attempted to use Wavelets for QRS detection [1,2,8,9,10] to overcome some of these issues. Wavelet analysis offer flexibility and adaptability and promises to overcome the limitations mentioned [2]. But along with the flexibility comes the price of determining the appropriate choice of the function and level of decomposition for this application. This paper reports efforts to determine the most suitable wavelets for the purpose of QRS detection.

II. A BRIEF INTRODUCTION TO WAVELETS:

A wavelet (time limited wave) is chosen as the "mother wavelet". This mother wavelet (ideally) is limited in time and frequency. Scaling and translation of the "mother wavelet" gives a family of basis functions called "daughter wavelets".

The Wavelet Transform of a time signal at any scale is the convolution of the signal and a time-scaled daughter wavelet. Scaling and translating the mother wavelet is the mechanism by which the transform adapts to the spectral and temporal changes in the signal being analysed.

Wavelets are generally orthogonal basis functions, though biorthogonal wavelet functions are now also being used. Orthogonality is considered an important property for the purpose of conserving the energy of the signal, an important property for reconstruction of the signal from the coefficients. Figure 1 shows the wavelet decomposition-

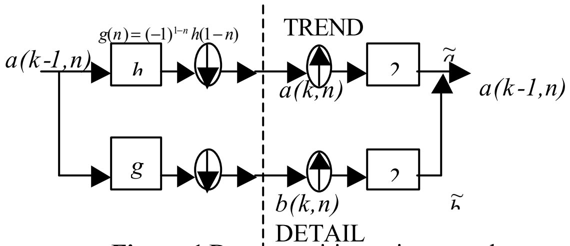

Figure 1 Decomposition using wavelets

reconstruction [11] of a signal. The signal is decomposed by the scaling and wavelet filter banks (coefficients $h(n)$ and $g(n)$) and down-sampled to get the trend and detail. The process is reversed to reconstruct the signal. The wavelet and scaling function coefficients are related by the equation 1.

$$g(n) = (-1)^{1-n} h(1-n) \quad \text{..........(1)}$$

The above relationship is for an orthogonal wavelet and scaling function. This is the simplest method and ensures conservation. But the orthogonal wavelets are unable to provide symmetry in the time domain and this results in an introduction of non-linear phase shift during

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Abstract

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analysis. This is a problem only if the temporal shape of the signal is important- as in the case of the ECG signal.

Biorthogonal wavelets have added complexity for the reconstruction of the signal due to the extra computation required for dual function but these wavelets offer temporal symmetry [11]. This prevents non-linear phase shift of the transformed signal. In the current problem, the shape of the signal in time domain is important while reconstruction of the signal is not required and this makes the choice of biorthogonal wavelets easier. The biorthogonal wavelet transform can also be represented by filters but with a difference as shown in figure 2 and equation 2. Here the decomposition/ reconstruction impulse repose are not the same and are related as described by equation 2.

$$\tilde{g}(n) = (-1)^{1-n} h(1-n)$$
$$\tilde{h}(n) = (-1)^{n} g(1-n) \quad \text{.......(2)}$$

The other important property of wavelets is their ability to localise temporal and spectral information- time and frequency localization. Time localization is generally inversely related to frequency localization and the smoothness of the wavelet function. A signal that has events that are separated by narrow frequency margins require frequency localization while signal where transitory

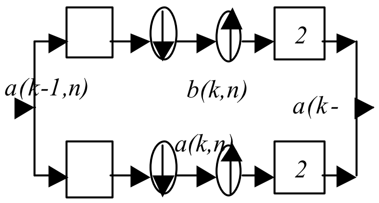

Figure 2 Decomposition using Biorthiogonal

events are important require time localization.

III. CHARACTERISTICS OF THE ECG

Figure 3 shows a typical electrocardiogram of a normal heartbeat recorded by lead II. Even though the 'standard' ECG is rather well defined, but ECG recordings of different individuals or an individual in different circumstances can differ significantly. Further, ECG recordings can have a number of other signals recorded alongside. This can be appreciated better in the frequency domain (5,6,7). The variation of the signal itself and presence of artifacts makes

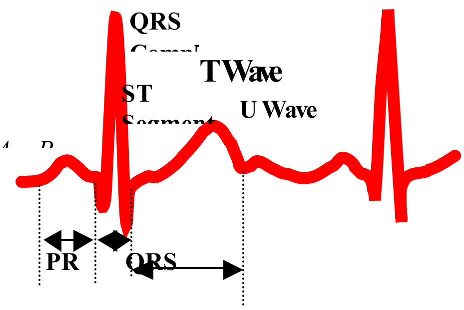

Figure 3: A Normal Heartbeat

the detection of the QRS difficult.

IV. WAVELET TRANSFORM BASED QRS DETECTION

The ECG is first segmented into L_w seconds and the DWT of each signal segment is computed [2]. The length of the segment reflects the tradeoff between the accuracy and computational time-consumption of the algorithm. Subsequent segments are obtained by overlapping the windows by 75%.

The algorithm locates the local maxima of the absolute value of the DWT that exceeds the given threshold for each scale. The threshold is chosen manually to minimise errors. This study determined empirically that the choice of 65%, 50% and 40% of the maximum value of the DWT in each windowed segment of data at scales $i = 1, 2$ and 3 respectively gave the best results. If the detected peak after thresholding appears in atleast two scales with a misalignment of less than ±0.1s (or ±25 samples), the algorithm considered that as a QRS complex. A peak occurring within the refractory period (0.2s) is disregarded. This reduces false positives. The location of the QRS complex detected is marked on the file.

V. WAVELET SELECTION

To determine the choice of wavelet, properties of the QRS were examined. There are three properties of the ECG that are useful for detection of the QRS complex; QRS has the highest slope; the shape of the signal is important; event is localised in time.

The shape of the signal is maintained if the phase shift is linear. Thus one requirement of the wavelet is that it should have a symmetrical function. Such wavelets are non-orthogonal.

Time localisation is important because the ECG events are transient.

Spline wavelets have properties satisfying the two requirements discussed above. They are first derivatives of smoothing functions and represent symmetrical filters. The family of Spline wavelets has its general Fourier transform as follows:

$$\hat{y}(w) = iw\left(\frac{\sin(w/4)}{w/4}\right)^{2n+1} \qquad (3)$$

where n = 0, 1, 2, 3..., corresponding to linear, quadratic, cubic, and higher-order spline wavelets.

The higher order of the Spline wavelet results in the sharper frequency response of the equivalent FIR filter. This is always desirable in wavelet transform. But the FIR equivalent filter of the higher order Spine wavelet is longer coefficient series, leading to more computational time-consumption. Therefore the cubic Spline wavelet is assumed to have a high enough order for this application. Figures 4 and 5 are examples of different wavelets and illustrate the quadratic and cubic Spline wavelet with their scaling functions respectively. The reader may refer to [11] for more details.

These functions can result in non-perfect reconstruction due to their not being orthogonal. In this application the reconstruction procedure is not taken

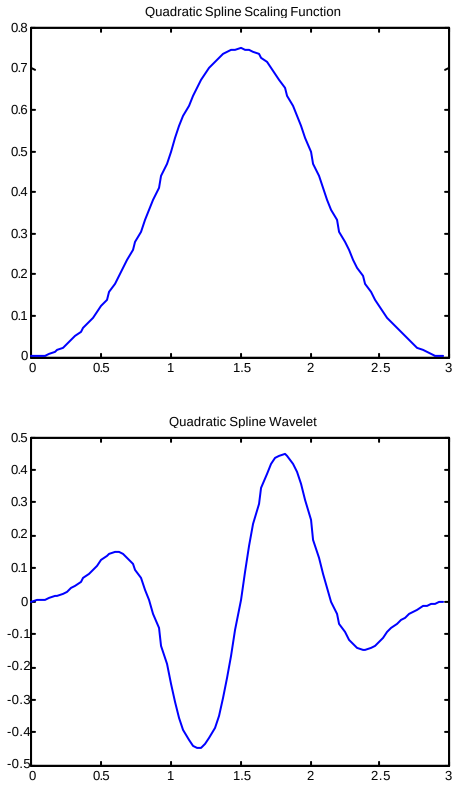

Figure 4: Quadratic Spline

required. Therefore, cubic and quadratic Spline wavelet maybe suitable for this application

The Haar wavelet on the other hand is compact in time and provides localisation in time and can be considered to be on the other extreme. It also provides ease in computation but does not provide the localisation in frequency. The dB3 wavelet is a wavelet function that includes partial properties for all the ECG signal requirements. This paper reports a comparison of these wavelets.

A. Data

The MIT-BIH database [13] was used for the analysis. The entire database consists tens of hours of ECG signal and has been distributed in CD-ROM format.

Some records are relatively clean and uncomplicated while others contain many ventricular ectopic beats and considerable level of noise. All records are dual channel ECG signals. Cardiologists have manually identified the time of occurrence and classified the type of QRS complex anomaly for each record making it suitable for this study.

B. Methodology for QRS Complex Detection

This paper reports on the analysis of the first four-minute signals of the 25 records in the data base. This amounted to a total of 100 minutes of data and more than eight thousand QRS complexes. Records were chosen with the intention of representing wide ranges of complexity and noise level.

Four different wavelets- Haar, Daubechies 3, Quadratic Spline and Cubic Spline were used. The QRS complexes detected using the wavelets were compared with the annotation file accompanying each signal file to determine the errors. The percentage of error (error rate =

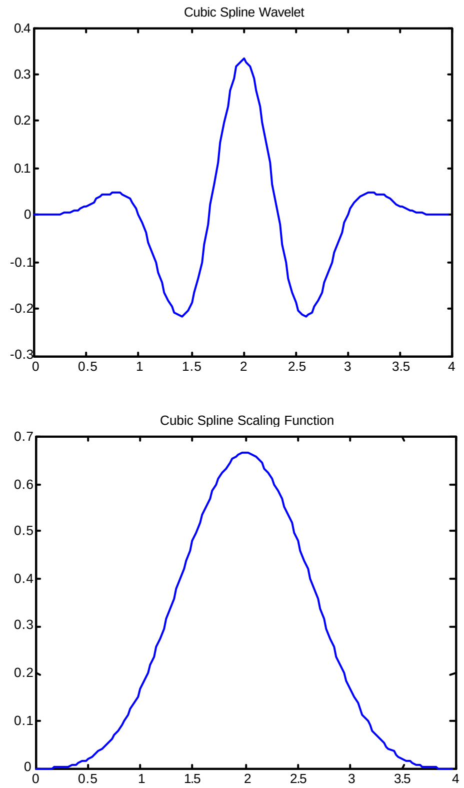

Figure 5 Cubic Spline

(FP+FN)/total number of beats) was taken as the criterion for comparing the results (FP denotes the number of false positives and FN denotes the number of false negatives).

VI. VII. RESULTS AND ANALYSIS

The overall technique (all the wavelet functions) was successful for 24 records out of 25. The one record – number 207-where the technique failed was where there was an occurrence of atrial flutter and the QRS complex did not have a high slope.

Figure 6 is a sample of the analysis.. The top plot presents a 2 second signal segment (500 samples). The three subsequent plots show the DWT computed using Cubic Spline wavelet at the scales $a=2^1$, 2^2 and 2^3 respectively. The marks indicate where the local maxima exceed the threshold. At scale $a=2^1$, six peaks exceed the threshold, three at scale $a=2^2$ and three at scale $a=2^3$. The algorithm determine QRS occurrences if there are two thresholded maxima at two sequential scales In this case, the first QRS complex is identified by the agreement between the second maxima at scale $a=2^1$ and the first one at scale $a=2^2$; the second QRS complex is identified by the agreement between the second maxima at scale $a=2^2$ and

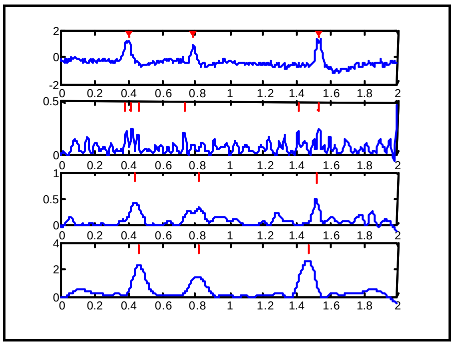

Figure 6:QRS Complex Localisation

the second one at scale $a=2^3$. Similarly, the third QRS is recognized by the last maxima at scales $a=2^1$ and $a=2^2$.

Table 1 shows the result of the experiment. It provides a comparison of the use of the different wavelets for detection of the QRS complex.

(LOCATION FOR TABLE 1)

VII. DISCUSSIONS

The results clearly demonstrate that the error in detection of the QRS complexes by this technique is very small. The mean error is down to 0.75%, a strong justification for the use of wavelets for QRS complex detection.

From the results, it can be observed that all the wavelets have very similar results for 90% of the ECG recordings (22 of 24 records). But for the balance 10%, Overall results demonstrate that the use of Cubic spline gives the least error while the use of Haar and quadratic Spline give highest error rates. It can also be observed that both, Haar and Cubic Spline give the maximum zero error for a record (six each).

Based on the results, it can be stated that Cubic Spline is more suitable for this application because it reduces the probability of error in the detection of the QRS complex. Thus it can be concluded that a wavelet with symmetrical function of high order is suitable for QRS detection.

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		Cubic B-spline				Quadratic B-				Db3				Haar			
Rec No.	Total QRS	FP	FN	TF	Error Rate	FP	FN	TF	Error Rate	FP	FN	TF	Error Rate	FP	FN	TF	Error Rate
100	297	0	0	0	0.00	0	1	1	0.34	0	0	1	0.34	0	0	0	0.00
101	279	2	0	2	0.72	2	1	3	1.08	2	3	5	1.79	2	1	3	1.08
102	294	0	0	0	0.00	0	0	0	0.00	0	2	2	0.68	0	0	0	0.00
103	282	0	0	0	0.00	0	0	0	0.00	0	0	0	0.00	0	0	0	0.00
104	297	10	1	11	3.70	18	1	19	6.40	17	4	21	7.07	29	1	30	10.10
105	334	0	0	0	0.00	0	0	0	0.00	0	1	1	0.30	0	0	0	0.00
106	269	0	2	2	0.74	0	18	18	6.69	0	8	8	2.97	0	17	17	6.32
107	283	0	0	0	0.00	0	1	1	0.35	0	1	1	0.35	0	0	0	0.00
118	290	0	0	0	0.00	0	0	0	0.00	0	0	0	0.00	0	0	0	0.00
119	261	0	1	1	0.38	0	8	8	3.07	0	4	4	1.53	0	9	9	3.45
200	339	2	8	10	2.95	4	4	8	2.36	3	1	4	1.18	7	1	8	2.36
201	356	0	1	1	0.28	0	2	2	0.56	0	0	0	0.00	0	3	3	0.84
202	212	0	0	0	0.00	0	0	0	0.00	0	1	1	0.47	0	0	0	0.00
203	402	2	12	14	3.48	3	8	11	2.74	2	7	9	2.24	5	6	11	2.74
205	359	0	0	0	0.00	0	0	0	0.00	0	0	0	0.00	0	0	0	0.00
208	414	0	2	2	0.48	0	10	10	24.15	0	67	67	16.18	0	10	10	26.09
209	379	0	2	2	0.53	0	0	0	0.00	0	1	1	0.26	0	0	0	0.00
210	357	0	8	8	2.24	4	6	10	2.80	0	7	7	1.96	4	6	10	2.80
212	369	0	0	0	0.00	0	1	1	0.27	0	0	0	0.00	0	0	0	0.00
213	441	0	1	1	0.23	0	7	7	1.59	0	7	7	1.59	0	7	7	1.59
214	309	1	2	3	0.97	2	3	5	1.62	2	2	4	1.29	2	4	6	1.94
215	455	1	4	5	1.10	1	4	5	1.10	1	2	3	0.66	1	4	4	0.88
217	290	0	0	0	0.00	0	0	0	0.00	0	0	0	0.00	0	0	0	0.00
219	441	0	1	1	0.23	0	2	2	0.45	0	2	2	0.45	0	3	3	0.68
Average Error Rate					0.75				2.32				1.72				2.54